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Analysis of machine learning-based applications for intelligent construction of shield tunnels

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Abstract. With the quick advancement of the level of information science in shield tunnel construction, the monitoring methods of shield equipment during tunnel boring work are increasingly improved and the recorded construction data includes not only information on the internal workings of the shield equipment, but also on its interaction with the external strata. Machine learning data analysis is powerful and has a wider range of applications and scope than traditional data analysis methods in the civil construction industry. Through the use of machine learning methods, the data and information collected can be mined and analysed in depth to find the intrinsic connections and linkages that can help improve the safety and efficiency ragarding shield tunnel construction. This work presents a literature analysis of current situations of machine learning for shield tunnel construction at home and abroad, briefly describes the basic principles of machine learning methods, summarises and analyses the research situation in shield tunnel construction, reviews the progress of machine learning-based shield equipment condition analysis, intelligent prediction and control methods for shield tunneling parameters and shield tunneling surface deformation prediction, and summarises the current research The study also summarises the shortcomings of current research. Finally, an outlook on the development of shield tunneling towards intelligence is presented.

Keywords: machine learning, shield tunnel, intelligent construction.

1. Introduction

With the advancement of urbanisation in China, urban population density and building density are increasing, and the planning and construction of underground space is in full swing and will be a key area of urban infrastructure construction for a long time. Tunneling has the outstanding advantage of not taking up surface land resources and can solve the urban surface congestion problem in an environmentally friendly and efficient manner, thus attracting much attention. At present, the main underground space construction needs in China are concentrated in densely populated and built-up areas, with diverse spatial planning and construction needs, and still face many difficulties in the stratigraphic exploration, tunnel design and construction stages. Among the methods of urban tunnel construction, the main ones are open-cut and concealed excavation, of which the concealed excavation method includes the mining method, the new Austrian method, the pipe jacking method, and the shield method, of which the shield method is highly efficient, stable, reliable, safe, and environmentally friendly. Recently, these methods are broadly applied in urban tunnel construction. Under such a development

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trend, how to intelligently regulate the shield construction process, control the disturbance and damage of the tunnel construction to the existing buildings and facilities in the surrounding area, reduce the risks that may be caused during the construction process, and ensure the safety and economy of the tunnel construction is an urgent need for the safe and efficient development of urban underground space in China [1].

Machine learning, as a branch of science of artificial intelligence, is widely used for research in computer vision, language recognition, natural language processing and physical computing. Because machine learning methods make full use of various engineering data, such as construction environment, stratigraphic conditions and engineering parameters, they not only reasonably consider various complex factors in tunnel shield construction excavation, but also possess real-time dynamic updating and prediction capabilities, which can accomplish efficient control and intelligent optimisation of tunnel shield construction, and are powerful in solving the problems of uncertainty and randomness encountered in tunnel shield construction, and therefore It has received the attention of many experts and scholars.

2. Principles of machine learning methods

Machine learning is a technique that requires the construction of algorithmic models and then automatically analyses the intrinsic relationships of data based on the input data to produce the resulting data. Machine learning provides good insight into the intrinsic relationships of data, which facilitates better decision making and prediction. Deep learning was invented when machine learning scholars discovered that artificial neural networks could learn how to capture the characteristics of data on their own, thus evolving a completely new approach to machine learning that is particularly suited to data such as sound, images, and text. Deep learning has greatly improved the efficiency and intelligence of machine learning algorithms by virtue of being based on artificial neural network algorithms that allow the data to build its own corresponding fundamental laws during the learning process. Today, machine learning and its related algorithms are broadly leveraged in many fields such as image processing, data mining, language recognition, etc. due to their efficiency and intelligence.

The key to machine learning is to train computers to imitate the human ability to "learn and grow from experience" by feeding them data, and to derive computational methods directly from "learning" data, rather than relying exclusively on pre-determined data models. With more training samples, the accuracy of the corresponding data model also improves, allowing for effective problem solving. There are four basic types of algorithms, including supervised, unsupervised, semi-supervised, and reinforcement learning. In addition, machine learning model building consists of the following basic steps: collecting data, pre-processing data, and extracting features, training the model, and tuning the model [2].

In the field of shield tunneling, some of the most frequently used basic machine learning models are support vector machines, neural networks, regression trees and random forests. If the above algorithms are effectively combined with other methods of artificial intelligence, the new synthetic algorithms obtained can greatly improve the effectiveness and accuracy of machine learning methods. At present, the application of them in shield tunnel engineering mainly includes the analysis of shield equipment status, estimation of tunneling performance, prediction of geological parameters and identification of surface deformation, etc [3].

3. Intelligent conditional analysis of shield equipment

Shield equipment is huge and consists of many parts, so it is prone to various mechanical failures during the specific construction process. Because of the dangerous construction environment and underground work, it is difficult to troubleshoot and solve problems when faults occur during the excavation process. As the main part of the shield equipment, the cutter plate, which is the main part of the shield equipment, fails at a high frequency during the construction process. To tackle the major problem of cutter disk failure, scholars have focused on applying these algorithms for solving the diagnosis method of high frequency failure of cutter disk.

Jin et al developed a method for real-time prediction of cutter disk torque of shield equipment based on multi-algorithm optimisation by establishing a functional equation for exclusion data in order to address the impact of invalid and abnormal data on the operation of shield equipment [4].

Elbaz et al combined genetic algorithms with neural network-based data pre-processing methods in order to effectively predict the service life of shield equipment tools [5]. Zou et al input the parameters of shield equipment excavation into an algorithm that can automatically retrieve features in order to reasonably diagnose faults that occur in shield equipment, and subsequently use the output data from the automatic feature retrieval as input data for a back propagation network to solve the prediction [6].

Because shield equipment is a dynamic construction operation, the analysis of data observation and analysis, which is merely stuck in static correlation, cannot effectively and rationally implement proper control and guidance for specific project works, so a state analysis method based on time-series features should be used to address the collection and analysis of dynamic feature data. Gao et al leveraged long short-term memory [7]. The experiments showed that the best results were obtained from the recurrent neural network model. Qin et al proposed a unification of long short-term memory model and convolutional neural network to extract sequential and implicit features for efficiently predicting the tool torque of shield equipment as a analyse and judge by the parameters of the shield equipment during operation [8].

The monitoring data during shield equipment operation and construction is complex and extensive. If unprocessed raw data is used for training, the expected high accuracy prediction model cannot be obtained, so the effectiveness of data pre-processing determines the correctness of the machine learning. It is well known that recurrent neural networks have powerful learning capabilities in terms of temporal features and are widely used for condition analysis of shield equipment. However, its shortcomings are the huge computational power requirement and slow training optimisation, so there is still a need to continue to expand the research in shield equipment condition analysis.

4. Intelligent prediction of shield excavation parameters

The performance indicators of shield equipment, such as soil bin pressure, propulsion rate and blade load, play a key role in the cost and schedule management of the project during operation and construction. Traditional research methods have relied on simulation, theoretical modelling and indoor model experiments to speculate on the construction performance of shield equipment during operation, but these methods have limitations and can usually only study one aspect of the shield equipment's performance characteristics. Nowadays, algorithms like neural networks, fuzzy mathematics and regression analysis can be used, combined with real data collected in the field, to effectively analyse the intrinsic correlation between the parameters of the surrounding rock and the equipment performance and condition indicators of the shield equipment during operation works, etc., and thus achieve the desired results.

Afradi et al leveraged neural network and support vector machine to estimate the penetration of shield equipment during the building of the Beheshtabad water transfer tunnel in Iran, and the analysis showed that the support vector machine approach was more reasonable and accurate [9]. Stypulkowski et al combined the surrounding rock parameters with the shield equipment operating parameters by constructing a neural network regression model to reasonably predict the shield equipment advancement, highlighting the powerful predictive nature of the relevant parameters [10]. To better address such problems, more efficient models like dynamic regression trees and deep neural networks have also been used to construct predictive models for job site data. Sun et al leveraged a random forest algorithm to estimate the advancement of shield equipment by combining information on the surrounding rock parameters and analysing the shield equipment's digging attitude [11]. In studying the direction of shield equipment attitude prediction and control. Zhou et al used a convolutional neural network feature extractors for a shield equipment tunnel state and position prediction framework to correctly decide the state and position of the shield equipment [12].

The above study shows that current machine learning methods have been studied in the important performance of shield equipment. Most of the data input to the prediction models are mainly geological exploration results and equipment parameters during the tunneling of shield equipment. The prediction results are generally first correlated with the input data to select a suitable input parameter, which is then imported to select the correct machine learning algorithm to train the model.

5. Intelligent prediction of ground deformation in shield excavations

The development of ground deformation resulting from the excavation of shield equipment is mainly in the following five stages: (1) prior settlement; (2) settlement in front of excavation; (3) settlement during advancement; (4) settlement in the void at the end of the shield; and (5) subsequent settlement. The above stages are corresponding to many factors such as geological status and construction site conditions. How to correctly and reasonably predict the ground deformation of shield equipment during the excavation process is the main direction of research by scholars at present. For minimizing the adverse effects of ground deformation on the surrounding environment during the excavation of shield equipment, scholars have used machine learning algorithms to effectively combine with ground deformation parameters to accurately assess the extent of ground deformation.

In using machine learning methods to study surface deformation, Sun Jun et al adopted the research method of artificial neural network technology in order to study the surface deformation and settlement caused by the tunneling of metro shield equipment, creating a neural network model and accurately estimating the appearance settlement in front of the working 5 m [13]. Chen et al used a comparative study of different common data mining methods to forecast the settlement derived from the construction of shield tunnels of settlement [14]. Kohestani et al compared two different methods, random forest and neural network, to forecast surface settlement due to tunneling of shield equipment and found that random forest predictions outperformed artificial neural network predictions [15]. Zhang et al predicted settlement due to tunneling and optimised the shield construction when settlement [16]. Pourtaghi et al combines neural networks and wavelet networks to maximise the prediction of surface settlement in order to reduce the hazards and risks associated with tunnel construction [17].

A summary of the research on surface deformation in shield tunnelling shows that as most of the shield equipment construction is in a complex underground environment, most of the monitoring data collected is featureless. Sensors are not only difficult to arrange in the underground space, but are also susceptible to complex site and construction conditions, often resulting in errors and missing monitoring data. Not only that, the large amount of invalid sample data can easily lead to insufficient training samples for machine learning algorithms, increasing the difficulty of predicting surface deformation in shield excavations. Therefore, scholars generally use data from the simulated state in the laboratory for the training of machine learning models. The numerical and feature differences between the simulated data and the collected data are analysed, and then a migration learning approach is used to rationalise the use of the simulated data obtained in the laboratory.

6. Conclusion

Machine learning methods are widely used in shield tunnel construction, reasonably improving safety and efficiency during operational construction. However, to truly realise the level of application of machine learning methods in practical engineering, the following aspects still need to be addressed and developed.

(1) Overfitting problems are seen everywhere in the use of machine learning methods during shield tunnel construction. Overfitting is often caused by overly complex models and insufficient sample sizes, and such problems become more common when a large number of various complex neural network models are used. Therefore, several different approaches can be taken to reasonably solve the overfitting problem for shield tunnel construction, such as expanding the samples, terminating training early, modifying the loss function, and replacing the algorithm.

(2) Enhanced machine learning algorithms using 5G technology and cloud computing methods. The training cost of machine learning models on shield tunnel construction is too high, and most of the model training is now mainly trained in the laboratory. If a combination of 5G technology and cloud computing is used as a training method, the corresponding data parameters are collected at the shield tunnel

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construction site, uploaded to the cloud for model training and prediction, and then the output data results are returned. This not only greatly reduces training costs, but also saves time, a research direction still worthy of scholarly exploration and study.

(3) Building a multi-functional intelligent platform to control the construction of shield tunnels. As multi-disciplinary cooperation in shield tunnel construction deepens, many data requires to be exchanged and shared, so it is imperative to build a multi-functional intelligent platform. It is more conducive to multi-disciplinary cooperation, improving the efficiency of cooperation and truly allowing the shield tunnel construction to develop in the direction of intelligence.

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